DAMEWARE

(Data Mining & Exploration Web Application and Resources)

on behalf of the DAMEWARE collaboration:

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Why Machine learning ?



The four legs of modern science

1. Experiment (ca. 3000 yrs)

2. **Theory** (few hundreds yrs) mathematical description, theoretical models, analytical laws (e.g. Newton, Maxwell, etc.)

3. **Simulations** (few tens of yrs) Complex phenomena

4. Data-Intensive science (now!!!)

http://research.microsoft.com/fourthparadigm/

"One of the greatest challenges for 21st–century science is how we respond to this new era of data intensive science"

ASTRONOMY CAN BENEFIT FROM WHAT HAPPENS ELSEWHERE



As a result of large surveys, astronomy has entered an era where



Most data will never be seen by humans!

The need for data storage, network, database-related technologies standards, etc.



Most knowledge hidden behind data complexity is potentially lost

Most (if not all) empirical relationships known so far depend on 3 parameters (e.g. fundamental plane of E galaxies and bulges). Simple universe or rather human bias?



Most data (and data constructs) cannot be comprehended by humans directly!

The need for data mining, KDD, data understanding technologies, hyperdimensional visualization, AI/Machine-assisted discovery



The various components of the data challenge



DAMEWARE

Is a web-based application (FREE AND OPEN TO THE PUBLIC) for massive data mining based on a suite of machine learning methods on top of a virtualized hybrid computing infrastructure

A joint effort between University Federico II, INAF–OACN & Caltech, aimed at implementing (as web 2.0 apps and services) a scientific gateway for data exploration on top of a virtualized distributed computing environment





Effective DM requires complex work-flows



DAMEWARE the GUI

| DAME Application - User: bresciamax@gmail.com | | | | | | | | | | | | LogOut 🤰 |
|---|----------------|---------------------|-------|--|--------------------------|----------------|------------------|---------------|------------------|-------------------------|---------------------|---------------|
| App Manuals • | Mo | odel Manuals 👻 | | Cloud Services 1 | • | Science | Cases 💌 | | Documents • | | Info 💌 | |
| RESOURCE MANAGER | | | | | | | | | | | | |
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| [4.]H | | | | | | | | | | | | |



DAMEWARE



It is multi-disciplinary platform (astronomy, bioinformatics and medical diagnostics)

End users can remotely exploit high computing and storage power to process massive datasets (in principle they can do data mining on their smartphone...)

User can automatically plug-in his/her own algorithm and launch experiments through the Suite via a simple web browser





GPU technology ... sometime useful

The Graphical Processing Unit is specialized for compute-intensive, highly parallel computation (exactly what graphics rendering is about).





Graphical capabilities in DAMEWARE

Histograms 2-D & 3-D plots Line plots Image visualization



Java client



AGN identification and classification

Photometric classification of emission line galaxies with Machine Learning methods, Cavuoti et al., 2013, MNRAS, submitted

Star/Galaxy separation

The detection of globular clusters as a data mining problem, Brescia et al., 2012, MNRAS, 421, 1155-1165 (arXiv:1110.2144) GPUs for astrophysical data mining. A test on the search for candidate globular clusters in external galaxies. S. Cavuoti, et al., New Astronomy, april 20, 2013, <u>http://dx.doi.org/10.1016/j.newast.2013.04.004</u> (astro-ph: 1304.0597)

Photometric redshifts

Mining the SDSS archive. I. Photometric redshifts in the nearby universe, D'Abrusco, Logno G., Walton N., 2007, ApJ, 663, 752

Astroinformatics of galaxies and quasars: a new general method for photometric redshifts estimation , O. Laurino, R. D'Abrusco, G. Longo, and G. Riccio, MNRAS, 2011, 418, 2165 (arXiv/1107.3160); Photometric redshifts with Quasi Newton Algorithm (MLPQNA) Results in the PHAT1 context, Cavuoti et al. 2012, , Astronomy and Astrophysics 546, 13, (ArXiv:1206.0876)

Photometric redshifts for quasars in multiband surveys, M. Brescia et al., 2013, ApJ, 772, 140 (astro-ph: 1305.5641)

Inside catalogs: a comparison of source extraction software, M. Annunziatella, et al., 2012, PASP, 125, 68 (astro-ph:1212.0564).

Other

Astroinformatics, data mining and the future of astronomical research, M. Brescia & G. Longo, 2012, invited to appear in proceed. of IFDT2 - 2nd International conference frontiers on diagnostic technologies (arXiv:1201.1867)

CLASPS: a new methodology for knowledge extraction from complex astronomical data sets, R. D'Abrusco, G. Fabbiano, S.G. Djorgovski, C. Donalek, O. Laurino & G. Longo, 2012, ApJ, 755, 92 (ArXiv: 1206.2919)

Current Applications in other fields

Medical diagnosis of alzhaimer (S. Cocozza et al.)

Brain tomography analysis (Bellotti M. et al.)

Real time classification of ethernet data flows (G. Ventre et al.)

Etc...

Some statistics (2013)

Ca. 100 users, > 12.000 experiments



An operative example

Use case:

Photometric redshifts evaluation for quasars in panchromatic surveys

Functionality: regression

Pre-processing: preparation of KB (10⁵ objects) removal of NaN, splitting of train, validation, test sets

Feature selection (>50 experiments)

Selection of best DM model: SVM; MLPBP, MLP-GA, GAME, MLPQNA

Training Validation (10 experiments) Test

TOTAL of ca. 2000 experiments

Visualization, comparison & Evaluation of results *Pucon, August 2013*



PHOTOMETRIC REDSHIFTS AS A INVERSE PROBLEM







| TEST | MEAN | σ | out. 1 σ | out. 2σ | out. 3σ | out. 4σ | TOTAL OBJECTS |
|------|---------|-------|-----------------|----------------|----------------|----------------|---------------|
| E5 | 0,0005 | 0,118 | 18,67% | 4,01% | 1,51% | 0,87% | 3787 |
| E16 | -0,0004 | 0,154 | 18,11% | 4,75% | 1,98% | 0,98% | 3787 |

Table 3. Summary of the statistical indicators alread used in Table xx (bias, σ and the percentage of outliers at, respectively, 1,2,3 and 4 σ computed as in citebovy2012 on all objects (test and training set).

| ZSPEC BIN | EXP | BIAS | SIGMA | $ \Delta Z > 0.1$ | $ \Delta Z > 0.2$ | $ \Delta Z > 0.3$ | $ \Delta Z > 0.4$ | OBJECTS |
|----------------|-----|---------|-------|--------------------|--------------------|--------------------|--------------------|---------|
| TRAIN Only | | | | | | | | |
| [0.2, 1.0] | E23 | -0.0897 | 0.206 | 44.94% | 22.78% | 13.29% | 8.86% | 316 |
| [0.2, 1.0] | E5 | -0.0183 | 0.118 | 27.53% | 7.28% | 2.22% | 1.27% | 316 |
| [0.2, 1.0] | E16 | -0.029 | 0.127 | 29.43% | 10.76% | 3.48% | 1.90% | 316 |
| [0.2, 1.0] | E10 | -0,1807 | 0,281 | 64,87% | 39,87% | $26,\!58\%$ | 18,67% | 316 |
| [1.4, 3.0] | E23 | 0.1209 | 0.273 | 59.05% | 32.33% | 21.98% | 14.22% | 232 |
| [1.4, 3.0] | E5 | 0.0364 | 0.18 | 38.36% | 14.66% | 8.19% | 4.74% | 232 |
| [1.4, 3.0] | E16 | 0.0408 | 0.183 | 40.09% | 15.52% | 8.62% | 4.74% | 232 |
| $[1.4, \ 3.0]$ | E10 | 0,2188 | 0,367 | 62,50% | $41,\!38\%$ | 28,88% | $22,\!84\%$ | 232 |
| TRAIN+TEST | | | | | | | | |
| [0.2, 1.0] | E23 | -0.0911 | 0.23 | 46.24% | 23.18% | 13.77% | 9.03% | 1583 |
| [0.2, 1.0] | E5 | -0.0174 | 0.101 | 21.04% | 4.17% | 1.58% | 0.82% | 1583 |
| [0.2, 1.0] | E16 | -0.0326 | 0.142 | 30.01% | 9.85% | 4.67% | 2.65% | 1583 |
| [0.2, 1.0] | E10 | -0,1877 | 0,287 | 63,93% | 39,55% | $27,\!48\%$ | 19,08% | 1583 |
| [1.4, 3.0] | E23 | 0.1238 | 0.269 | 56.24% | 30.74% | 18.69% | 12.49% | 1145 |
| [1.4, 3.0] | E5 | 0.0271 | 0.139 | 31.44% | 9.61% | 3.93% | 2.10% | 1145 |
| [1.4, 3.0] | E16 | 0.0492 | 0.183 | 39.83% | 14.93% | 7.95% | 4.37% | 1145 |
| [1.4, 3.0] | E10 | 0.2488 | 0,37 | $64,\!28\%$ | 44,02% | 32,23% | 24,72% | 1145 |

The new mantra

Discovery of rare and unknown...

Search for higher order correlations etc...

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Small data sets: serendipity or guided luck

Large Data sets: clustering....

The new mantra

Discovery of rare and unknown...

Search for higher order correlations etc...



Exploration of PS with N >10⁹, D>>100, K>10 Is anything but simple

N = no. of data vectors, D = no. of data dimensions K = no. of clusters chosen, K_{max} = max no. of clusters tried I = no. of iterations, M = no. of Monte Carlo trials/partitions



K-means: $K \times N \times I \times D$ Expectation Maximisation: $K \times N \times I \times D^2$ Monte Carlo Cross-Validation: $M \times K_{max}^2 \times N \times I \times D^2$ Correlations ~ N log N or N², ~ D^k (k ≥ 1) Likelihood, Bayesian ~ N^m (m ≥ 3), ~ D^k (k ≥ 1) SVM > ~ (NxD)³

Lots (...truly lots and lots...) of computing power

Moving programs not data: the true bottle neck **Data Mining + Data**

Warehouse = Mining of Warehouse Data



- For organizational learning to take place, data from must be gathered together and organized in a consistent and useful way – hence, Data Warehousing (DW);
- DW allows an organization to remember what it has noticed about its data;
- Data Mining apps should be interoperable with data organized and shared between DW. Interoperability scenarios



Full interoperability between DA (Desktop Applications) Local user desktop fully involved (requires computing power)





Data+apps Full WA → DA interoperability Partial DA \rightarrow WA interoperability (such as remote file storing) MDS must be moved between local and remote apps user desktop partially involved (requires minor computing and storage power) Except from URI exchange, no interoperability and different accounting MDS/must be moved between remote apps (but larger bandwidtbomputing power required

The Lernaean Hydra KDD

After a certain number of such iterations...



The scenario will become:

No different WSs, but simply one WS with several sites (eventually with different GUIs and computing environments)

All WS sites can become a mirror site of all the others

The synchronization of plugin releases between WSs is performed at request time

Minimization of data exchange flow (just few plugins in case of synchronization between

MDS!



WAy Py-1 Py-2 **Py-...** Py-n **Px-1 Px-2** Px-3 **Px-...** Px-n



astronomical problems are a piece of cake....

Growth of digital data worldwide (2012) 1 ZB/yr or = 10⁹ Terabyte

(), IT agility. Your way

The Data Growth Monster How Much Digital Information Exists in the World Today?







The Data Growth Monster How Much Digital Information Exists in the World Today?

NSA listening station in Bluffdale, South Dakota

1 YB of storage = 10^{12} TB Indexed, searched, mined...

With mainly unknown technology which will slowly leak out to the scientific community astronomical problems are a piece of cake....

Growth of digital data worldwide (2012) 1 ZB/yr or = 10⁹ Terabyte





Thanks for the attention and to Eduardo for organizing the meeting ...